Are automatic systems the future of motorcycles safety? Using a novel methodology to prioritize potential safety solutions based on their projected effectiveness.

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ABSTRACT

Objective: Motorcycle riders are involved in significantly more crashes per kilometer driven than passenger car drivers. Nonetheless, the development and implementation of motorcycle safety systems lags far behind that of passenger cars. This research addresses the identification of the most effective motorcycle safety solutions in the context of different countries.

Methods: A knowledge-based system of motorcycle safety (KBMS) was developed to assess the potential for various safety solutions to mitigate or avoid motorcycle crashes. First, a set of 26 common crash scenarios was identified from the analysis of multiple crash databases. Second, the relative effectiveness of 10 safety solutions was assessed for the 26 crash scenarios by a panel of experts. Third, relevant information about crashes was used to weigh the importance of each crash scenario in the region studied. The KBMS method was applied with an Italian database, with a total of more than 1 million motorcycle crashes in the period 2000–2012.

Results: When applied to the Italian context, the KBMS suggested that automatic systems designed to compensate for riders' or drivers' errors of commission or omission are the potentially most effective safety solution. The KBMS method showed an effective way to compare the potential of various safety solutions, through a scored list with the expected effectiveness of each safety solution for the region to which the crash data belong. A comparison of our results with a previous study that attempted a systematic prioritization of safety systems for motorcycles (PISa project) showed an encouraging agreement.

Conclusions: Current results revealed that automatic systems have the greatest potential to improve motorcycle safety. Accumulating and encoding expertise in crash analysis from a range of disciplines into a scalable and reusable analytical tool, as proposed with the use of KBMS, has the potential to guide research and development of effective safety systems. As the expert assessment of the crash scenarios is decoupled from the regional crash database, the expert assessment may be reutilized, thereby allowing rapid reanalysis when new crash data become available. In addition, the KBMS methodology has potential application to injury forecasting, driver/rider training strategies, and redesign of existing road infrastructure.

Keywords: Powered two-wheeler; road crash; motorcycle crash; motorcycle safety; collective knowledge; prioritization; policymaker

INTRODUCTION

Motorcycle safety research aims to contribute to the understanding of motorcycle crashes and their causes in order to make motorcycling safer. Its societal relevance is increasing due to the proliferation of powered 2-wheelers, or PTWs, and in the literature the safety problem is analyzed by continent and technological solutions are discussed (Blackman and Haworth 2013; Brown et al. 2015; Haworth 2012; Jamson and Chorlton 2009; Rogers 2008; W. H. Schneider et al. 2012; Sekine 2014). Clearly, PTWs offer advantages such as saving time when traveling on congested roads and requiring less parking space compared to cars (Wigan 2000). Considering the air pollution (Colvile et al. 2001; Shuhaili et al. 2013), many cities have implemented electric 2–/3-wheeler sharing programs (Barcelona, Grenoble, Toulouse, Paris), and future car-free initiatives (Brussels, Dublin, Madrid, Milan, Paris, and Oslo) allow the utilization of PTWs.

Nevertheless, the protection of motorcyclists is a pending issue. The societal cost of PTW crashes is high, and though passenger car safety have improved dramatically in the past decades (Glassbrenner 2012; Orsi et al. 2012), PTW safety has improved only marginally (Broughton et al. 2013; Deutermann 2004; NHTSA 2014; Nicol et al. 2012; Sekine 2014). This might be explained via the multidisciplinary complexity of PTW safety (motorcycle dynamics, rider/driver behavior, etc.), which is a challenging subject to be addressed by the relatively small PTW industry (11.9 million of cars yearly registered in European Union versus 1.0 million PTWs (ACEA 2013; ACEM 2014). Therefore, the question is how to channel the constrained economical resources of the PTW industry to the most promising solutions in motorcycle safety. This article presents a method for prioritizing PTW safety solutions. Ideally this would derive from a prediction of benefits in terms of fatalities, injuries, and costs. However, a quantitative prediction is hardly possible due to the nature of certain safety technologies (e.g., diverse settings in a traction control system can modify the vehicle dynamics in different emergency situations). Thus, we will introduce the safety function (SF) principle and test its effectiveness using crash data.

Unfortunately, current motorcycle crash databases are not harmonized (IMMA 2014), and their combined use can be demanding. Alternatively, the prioritization can be conducted based on expert opinions. However, the field of vehicular safety is characterized by a plethora of expert knowledge among a variety of specializations (e.g., crash analysis reconstruction, crash test analysis, energy absorber design, traction and braking control, traffic control, forensics, driver/rider training, injury treatment, etc.) that are not linked. Thus, there is a need to exploit this distributed knowledge and to combine it with crash statistical data in a systematic and constructive manner.

The aforementioned reasons, in particular the effort required for exploiting heterogeneous crash data, and the variety of expertise scattered among different scientific fields motivated us to develop a new methodology for PTW safety. Aiming to manage quantitative, imperfect, and unharmonized information, enabling the storage, analysis, and reuse of "collective expert knowledge" for wise decision making.

This article is organized as follows: First, a brief explanation of the only reference study (PISa project) that attempted a prioritization method for motorcycle safety technologies; second, the core of the method is explained for which comprehensive definitions of knowledge base (KB) and knowledge-based system (KBS) are provided; third, the methodology is explained and illustrated by a case study; fourth, a comparison is performed with PISa project outcomes; finally, the discussion is presented.

OVERVIEW OF PISA PROJECT

The European Commission–funded PISa project (2007–2012 Grant No. 031360) included in-depth reconstruction of 60 motorcycle crash cases (sampled from the UK On-The-Spot study and 2 German databases:

Forensic and COST 327). Some of them were physically emulated (videos taken from the vehicles approaching the place where the crash occurred), providing more insights into the crash scenario. All crashes were classified in a set of 7 relevant motorcycle crash scenarios defined in the APROSYS project (APROSYS 2009). The study identified 43 PTW safety solutions to be assessed. An international team of researchers active in the field of traffic crash analysis and prevention (2 coauthors involved) used the information on each crash case to establish how effective each safety system could have been, had it been present in each case. Finally, the safety systems were prioritized weighting the applicability in each of the crash cases based on the relevance of each of the 7 crash scenarios. The final priority list was published as an internal project deliverable. The PISa priority list will be presented and compared with results of our methodology, which is a generalization of the approach of the PISa project.

FUNDAMENTALS AND CORE OF THE KNOWLEDGE-BASED SYSTEM OF MOTORCYCLE SAFETYDEFINING A KNOWLEDGE-BASE

Defining a Knowledge-Base

Definition 1: A KB is an organized repository of facts and expert understandings about a particular aspect of reality. Its content is systematically classified and adapted to be computed by a machine.

The information collected includes objective variables (quantitative) and subjective or categorical ones (qualitative). They are stored in a codified manner, allowing for the combination of new information with the knowledge previously acquired.

This current definition is aligned with broad concepts and particular definitions of KBs developed in the field of artificial intelligence since the 1970s. At that time, the topic was called expert systems (Buchanan and Feigenbaum 1978; Chapman and Pinfold 1999; Hayes-Roth 1985; Minsky 1974; Waterman 1976, 1978, 1986; Waterman and Jenkins 1976).

Defining a Knowledge-Based System

Definition 2: A KBS is a tool that by computing on the KB allows reasoning with the content of the KB, presenting the characteristics of the case analyzed to the user, enabling a well-grounded decision-making process.

The utilization of a KBS in a specific field is intended to emulate some aspects of human cognition (such as memory, reasoning, and decision making), but it differs in the fact that memories come from the interpretation of experimental data and the contributions of many persons with expertise in this field.

Current successful applications of KBS as tools for decision making can be found in the following fields: Medicine (Gennari et al. 2003; Pavlovic-Veselinovic et al. 2016; Shortliffe 1976; Warner 1968), pharmacogenomics (Thorn et al. 2013), engineering design applications (Blount et al. 1995; Quintana-Amate et al. 2015; Sainter et al. 2000; Shaw and Gaines 1987; Verhagen et al. 2012), environmental science (Orgiazzi et al. 2016), research operations (Negre et al. 2015; Radivojevic and Milbredt 2016), corporative management (Grant 1996; Meso and Smith 2000; Soliman and Spooner 2000), energy production (Law et al. 2016), automotive (Chapman 2001), and aeronautics (Xu et al. 2012; Zhu et al. 2012).

In conclusion, the KBS approach can be very useful in multidisciplinary fields that have to deal with imperfect information (subjective or categorical variables). Accordingly, we applied it to motorcycle safety.

Safety Function concept

Definition 3: An SF unequivocally describes the desired outcome for a safety solution, emphasizing goals regardless of the constitutive mechanisms or subsystems.

The SF concept allows an easy evaluation of the potentiality of the safety solution among different scenarios. Next, an example illustrates how an SF may be accomplished by a combination of different safety systems.

Example of an SF: Ensuring the maximum longitudinal deceleration possible in a variety defined road surface conditions. Possible safety systems needed to accomplish this SF include the following:

1. Antilock braking system: An automatic system that acts on the wheel brakes to maintain tractive contact with the road surface according to driver inputs while braking, preventing wheels from locking up to avoid skidding;

2. Combined braking system: Automatic system that distributes the braking action between both wheels of the PTW, even if the rider's action consists of pure frontal or rear braking;

3. Active suspension: An automatic system that acts on the suspension performing quick damping changes to maximize the braking capabilities (by restraining PTW pitch, height of center of gravity, and wheelbase during the load transfer); and more systems can enlarge this case.

Aim and main features of the KBMS

The knowledge-based system of motorcycle safety (KBMS) is a KBS that intends to capitalize on the scattered knowledge about vehicular safety with emphasis on motorcycles or PTWs. The KBMS allows for the creation of a hierarchical list of SFs or safety solutions for PTWs, based on traffic crash information and expert judgments about possible crash countermeasures. The process consists of 2 separate stages (collecting and processing), allowing for the delocalization of actors involved. These stages are strictly defined for an operational framework.

METHODS

This section explains how to build each piece of the KBMS and how to implement the method (Figure 1). Each part of the methodology is complemented with a short example to illustrate the concepts.

Defining the evaluation framework

The framework defines the type of data to be used during the analysis and how to use it in order to obtain useful information. For the application in motorcycle safety, we defined 4 pillars based on (1) a definition of the road crash scenarios; (2) database segmentation obtained by applying a set of queries; (3) a definition of SFs to be evaluated; and (4) a definition of how to perform the evaluation.

Road Accident Scenarios

Road crash scenarios are a way to represent the circumstances of a crash (e.g., type of road; trajectory of the vehicles; and type of collision). Generally, all of the information is summarized in a pictographic system and each road crash database contains its own representation. Therefore, in order to be able to employ the methodology with different crash databases, it is necessary to create a common subset of crash scenarios. Finally, these crash scenarios will be used by safety experts at the collecting stage.

Example: The 26 representative crash scenarios for motorcycle crashes of the KBMS (default evaluation framework) have similar features of the scenario description of in-depth and national road crash databases (e.g., VALT, DaCoTA, Vic Roads, GDV, and CADaS). The pictograms are provided as a downloadable and editable resource (see Appendix A, online supplement).

Set of queries

To select the crash cases for the analysis, the investigators must express what they wish to consider by means of queries. Queries should be in a form that a database manager can use to extract road crash information (database segmentation) at the collecting stage. The database manager will provide the outcome of the queries in a predefined form.

Example: In our framework, 9 queries are defined (Appendix B, see online supplement) to group the 26 crash scenarios into 9 general scenarios, labeled A to I (Appendix A).

List of Safety Functions

In the KBMS method, a list of SFs is required for expert assessment at the collecting stage. A given set of SFs may represent, for example, the most promising solutions to develop. To evaluate existing safety systems, it is convenient to convert them into SFs, because the SF concept can be assessed with less information than a safety system/technology. In fact, a decision on the latter may require explicit crash tests or simulations. Additionally, the formulation of nonexistent SFs is an innovation enabler.

We elaborate a list containing 64 SFs for PTW application from available safety systems/technologies and conceptual ones (Appendix C, see online supplement). The review explored the automotive market, specialized literature in vehicular safety (Anderson et al. 2011; Bayly et al. 2006; Corno et al. 2008; Gail 2009; Savino et al. 2012, 2014, 2016; Van Elslande et al. 2012), inertial sensors (Corke et al. 2007), PTW safety technologies (Corno et al. 2015; Garcia et al. 2013; Montanari et al. 2011; Mukhtar et al. 2015), and how remote sensing for scene understanding (Mukhtar et al. 2015) could be beneficial, mainly based in stereo vision (Barth et al. 2009; Pfeiffer and Franke 2011; Rovira-Más et al. 2009; Suganuma and Fujiwara 2007), LIDAR (Homm et al. 2011; Navarro et al. 2016) and RADAR (Andres et al. 2012; Kellner et al. 2016; M. Schneider 2005). Finally, we ensure that the safety solutions evaluated in the PISa project all fit at least in one of the SFs from our broader list.

The expert assessment

Each expert involved in the process estimates the potential of each SF evaluated in each motorcycle road crash scenario. For consistency in the scores assigned among the evaluators, a common understanding of the scoring scale is needed.

The scale provided in Table 1 is conceived as a binary scaling method in order to avoid neutral responses such as "maybe" or "sometimes." Negative responses to a statement are (0, 1, 2) and positive responses are (3, 4). The score scale pertains to the ratio scale classification in the field of statistics and quantitative research methodology (Likert 1932).

Defining the knowledge base implemented

The KB capitalizes on human expertise in the road safety field by encoding and storing the judgments from expert assessment. The judgments are encoded in a manner that allows comparing the assessment between different experts and performing calculations.

KB example: We define a multidimensional matrix that contains numerical values (Figure 2); each cell corresponds to an SF ranked by a human expert (according to Table 1). Each cell is indexed for 5 characteristics: (1) road crash scenario (26 types); (2) SF (64 types); (3) objective (avoidance or mitigation); (4) expert category (e.g., biomechanics, passive safety, active safety, crash reconstruction, and other); and (5) individual expert (anonymized information). In the present example, theresultisa26×64×2×5×3matrixfilledwithvaluesfrom 0 to 4.

Defining the Inference Engine

In any KBS, the crucial element is the way of processing information with knowledge, which is commonly called an inference engine (IE). The processing stage can be done by logic-based rules or mathematical calculations. In particular, we defined the IE of the KBMS as a set of algebraic equations with the goal of prioritizing SFs for different road crash scenarios. Our IE conducts the prioritization of SFs according to Equation 6 by combining 2 kinds of information (Figure 1): The statistical relevance of each type of crash with respect to the region of study (given by Equation 3) and the potentiality (given by Equation 5) of each SF applied to particular crash configurations (contained in the KB).

The complete mathematical formulations are presented below, distinguishing between core calculations and complementary calculations.

Core of the KBMS inference engine

The equation set 1–3 refers to regional statistical road crash information; the equation set 4–5 refers to the KB. Finally, Equation 6 combines both types of information (end of the inference process).

Crash quantity coefficients.

$$Q_{i_n}|y = \frac{Q_i|y}{Q_y} \tag{1}$$

where i is the crash scenario number; y is the year of statistical crash data; Qi|y is the number of PTW crashes in scenario i during year y; Qy is the number of total PTW crashes during the year y; and Qi_n|y is Qi|y normalized to the total PTW crashes of the year.

Relevance coefficients.

To obtain the relevance level of each crash scenario type, we compute the weighted mean for the last years of each crash scenario. The weights defined by the default framework are included in a vector of 3 elements called a kernel. Different kernels compute annual, biannual, and trien-nial information.

$$Kernel_j = \{K_{j|y-2}; K_{j|y-1}; K_{j|y}\} \tag{2}$$

$$R_i = \frac{K_{j|y-2} \cdot Q_{i|y-2} + K_{j|y-1} \cdot Q_{i|y-1} + K_{j|y} \cdot Q_{i|y}}{\sum Kernel_j} \tag{3}$$

where Ri is the relevance of crashes in the scenario *i* and *j* is the kernel number.

Effectiveness matrix.

The effectiveness matrix contains coefficients that are computed from the KB (expert knowledge produced during the expert's assessment). Note that this matrix is composed for a set of matrices that pursue different goals (Equation 4); thus the contents of these are not a mix of them. We composed a large effectiveness matrix (Equation 5) only for calculation purposes.

$$Assessment\ type_r|k,i = \frac{1}{\sum i|pss} \cdot \sum_{pss} \frac{V_{k,i|pss}}{m_{k,i|pss}} \tag{4}$$

$$E_r|k,i = \left[Assessment\ type_1|k,i;\ \cdots; Assessment\ type_r|k,i\right] \tag{5}$$

where k indicates the safety function number; Type r refers to the kind of analysis performed (e.g., avoidance or mitigation analysis in our study); pss means a particular subscenario; i|pss refer to the particular subscenario of the ith crash scenario; Vk,i|pss indicates the numerical value of the assumed effectiveness of the safety function k for scenario i|pss; mk,i|pss, is the number of experts performing the assessment on the safety function k and also in scenario i|pss; and Er|k,i is the effectiveness matrix that represents the effectiveness of the function k under scenario i with regard to the type of goal r.

Importance matrix coefficient.

The importance matric coefficient highlights the statistically significant cases of the effectiveness matrix for the particular country or region under analysis. This matrix is calculated by weighting the effectiveness matrix with the relevance of each crash scenario according to the crash data employed.

$$I_r|k,i = R_i * E_r|k,i \tag{6}$$

where Ir|k,i is the importance of the safety function k for crash scenario i with regard to the type of safety goal r.

Output list.

The output list consists of the summation of all importances (one-dimensional array) by each SF and ordering the new one-dimensional array from the highest numerical value to the lowest one. Large numbers represent more important SFs.

Complementary metrics of the KBMS inference engine

The following metrics play a key role in the KBMS aiming to quantify and control the undesirable effects produced for errors or missing data in the crash accident database used. In our application case, 3 years of data from the ISTAT database (ISTAT n.d.) (205,272 PTW crashes from 2010 to 2012) were used to compute the next 2 metrics.

Coverage metric > 90%.

The default framework has 9 general road crash scenarios. These are a simplification to perform the global traffic crash analysis. Consequently, not all possible PTW crashes are included in these cases. The coverage metric computes the sum of all PTW crashes that occurred in the 9 general crash scenarios types (defined in Appendix B) and compares this to the total yearly PTW crashes. We adopted a minimum of 90%, implying that all crashes considered in the general crash scenarios must cover more than 90% of the total PTW crashes that occurred in this period. In the case that the value is less, more crash scenarios must be considered in order to obtain acceptable representation of reality.

Crash trends by scenario.

Using information from the last years it is possible to compute the trends in each crash scenario type. This provides a ratio of crash occurrence by time for each scenario, using the previous year as a percentage reference. Abrupt changes in these ratios can indicate inconsistency or errors during the segmentation process.

Collection Stage

The collection stage consists of 2 parts. From available crash data, the first part selects the crashes belonging to each scenario type based on the segmentation (queries in Appendix B) of road crashes. The second part is the assessment conducted by experts in road safety, which adds knowledge to the KB, as explained next.

Experts are professionals with recognized knowledge in their field and can come from a variety of disciplines (e.g., crash analysis reconstruction, crash test analysis, energy absorber design, traction and braking control, traffic control, driver/rider training, injury assessment, etc.). Recruited experts (see selection criteria in Appendix D, online supplement) are provided with guidelines (Appendix E, see online supplement) to conduct the assessment and with a clear terminology (Appendix F, see online supplement) defined to facilitate the participation of experts from different fields.

An example of expert assessment is depicted in Figure 3. A rating table (Table 1) is employed to assess the possible effectiveness of a set of SFs (Appendix C) in a set of road crash scenarios (Appendix A).

Regarding the incorporation of new assessments to the KB (collective knowledge), a 2-step coherence verification test is performed on the new information. To this end, a Fleiss's kappa calculation (Fleiss 1971) was performed to detect random answers in the compilation of the assessment reports by calculating the interrater agreement for qualitative items (Carletta 1996; Gwet 2008). The calculation can be made via spreadsheet, as explained by Zaiontz (2015). A second step consists of examining the ratings of each new assessment report, where the number of positive and negative scores for each case (3 to 4 and 0 to 2, respectively) is compared against the corresponding mean scores previously stored in the KB. This coarse check is able to identify possible misinterpretations in the evaluation, which require contacting the expert who performed the given assessment for clarification. Once validated, expert ratings are incorporated into the KB to be used in the following stage of the analysis. Otherwise, the person in charge of the KBMS must interview the expert who performed the evaluation to identify the misunderstanding, solve it, and request a new assessment.

Processing Stage

In the processing stage (Figure 1), the IE combines the 2 types of information received in order to compute an organized list of SFs. The list presents the SFs for motorcycles with the most potential to improve vehicular safety in the region of study.

CASE STUDY: KBMS-ISTAT

We implemented the complete KBMS workflow (Figure 1) employing (1) 3 years of road crashes (ISTAT 2010–2012) and (2) the assessment of experts in the motorcycle safety field.

Italian road data (more than 1 million PTW crashes) were used to identify the main trends among a variety of motorcycle crash scenarios in Italy. The 26 detailed crash scenarios of the KBMS method were clustered into 9 general crash scenarios (Appendix A) according to the information gathered from the ISTAT database (Table 2) by using the 9 queries of the default evaluation framework (Appendix B).

Independent of the road data analysis, a team of 3 experts was recruited in 2016. They analyzed the 26 crash scenarios to define the potential of each SF to avoid and/or mitigate the crash (10 SFs in this case study). The assessment was expressed in a scoring report (Figure 3), aiming to feed the KB of the KBMS.

Finally, during the processing stage, a metric for each SF was computed by the IE generating a prioritized list of SFs (Table 3). This list represented the collective knowledge stored until that moment in the KB of the KBMS.

Results and interpretations

Our case study (KBMS-ISTAT) used 205,272 PTW crashes that occurred in Italy in the period 2010–2012 (Table 2). The crashes analyzed involved at least one PTW (moped powered less than 50cc, scooter, or motorcycle) and resulted in at least one injured or killed person. With the crash classification of the KBMS default evaluation framework (Appendix A), we observed the following percentages regarding the total PTW crashes: (a) 51% were represented by only 4 types of crash scenarios (namely, A, H, F, and C); (b) 25% occurred at intersections (scenarios A and B) with a clear predominance of angular collisions; (c) 12% occurred in angle collisions in straight road segments (scenario H); and (d) 11% were rear-end collisions (scenario F). The trend for PTW crashes slowly decreased over the years in all cases except for the roundabout scenario, which increased in the same period. However, the increasing trend in the number of crashes in roundabouts could be due to the process of replacing standard intersections with roundabouts. Italy performed the replacements during the years analyzed and the safety performance of the roundabouts is under study (Giuffrè et al. 2015; Montella 2011; Pecchini et al. 2014; Sacchi et al. 2011).

A prioritized list of SFs is obtained by applying the KBMS approach in our case study (Table 3). The SFs with higher priority are those with potential to avoid and mitigate the greatest possible number of motorcycle crashes in Italy. The top 3 SFs were "Assist the rider to perform a hard braking without falling from the PTW," "PTW autonomous braking," and "PTW sends a signal to slow/stop other vehicle." At the bottom of the prioritized list we found "Driver state detection," "Other vehicle alcohol interlock," and "PTW lane keeping." Concerning the reasons for the lowest scored SF (PTW lane keeping), the rating reflects the fact that this function is obviously inadequate for urban motorcyclists. This finding becomes explicit by comparison of the numerical metric of this SF (0.14) with regard to the preceding ones (scored 0.74 and greater than 1.32). To support this result, we can highlight the practice of lane-splitting commonly observed in dense traffic (Aupetit et al. 2015).

We compare our outcome score list of SFs (analysis KBMS-ISTAT) against the findings of the PISa study (Table 3). The comparison reflects good correspondence in the top 3 and bottom 3 SFs of the prioritized lists, notwithstanding the different approaches, expert subjects, and crash material. A more detailed comparison would be possible, but it would also be quite complicated due to a number of factors, including periods and places of the crash data as well as methodological factors.

Finally, by using the KBMS method, we identified that 35–50% of PTW crashes in Italy could have been positively influenced by mitigating and avoidance SFs. The top scores of automatic systems to assist the rider during the crash precipitation event suggest an important role for these SFs. In practical terms, for the first 2 SFs in the ranking, equivalent safety systems in cars are currently available, namely, antilock braking system + electronic stability program (ABS+ESP) and autonomous emergency braking (AEB). The effectiveness of ABS+ESP and AEB for passenger cars was demonstrated in real cases (Burton et al. 2004; Fildes et al. 2015; Lie et al. 2004). However, the solutions for motorcycles still need to be clearly defined, and the KBMS method can contribute to this end.

DISCUSSION

The use of PTWs is high in Italy compared to the rest of Europe (Ordonez 2016; Schaller and Perlot 2016). PTW rider fatalities are high as well: 34% of the total road deaths in 2008 versus 19% in the rest of Europe (International Traffic Safety Data and Analysis Group 2010). Italian PTW crashes were studied carefully (Cafiso et al. 2012a, 2012b; Montella 2011; Montella et al. 2012). However, in motorcycle safety, the main constraint is the subjectivity of certain analyses due to the variability in the dynamics of the PTWs, the nature of the information and the judgments being made, as well as the methodology adopted. In order to overcome the difficulties, the authors propose the KBMS as a constructive, flexible, and scalable methodology. Why constructive? Additional experts' contributions for the assessment of crash scenarios will lead to more accurate predictions about the solution's performance. Why flexible? The evaluation framework allows the reorganization of crash scenarios and the modification of the IE according to the crash data available. Why scalable? The evaluation framework also allows the addition of new crash scenarios, new SFs, and new objectives such as injury criteria, medical costs, convalescence days, etc.

The KBMS is not a single study; it was conceived to be updated (using fresh crash statistical data) and reused over the course of time. Another advantage of this method is the step of information extraction from crash databases, which allows for confidentiality of the original crash data, as well as collaborative sharing of the data.

To the best of the authors' knowledge, the safety system prioritization performed in the PISa project was the most comprehensive in terms of safety systems evaluated that focused on motorcycle technologies. A subset of results of PISa pointing out the most prominent safety solutions for motorcycle safety is presented in Appendix G (see online supplement). Thoroughly analyzing the documentation of the PISa project, we found no distinction between SFs and safety systems/technology. Consequently, during the assessment phase, experts were requested to evaluate the functionality of a safety solution or the performance of a specific technology without any distinctions between the potential benefits of a theoretical function and those of a practical system. Assessing how a technology may behave in a given circumstance requires more accurate information than the evaluation of a specific functionality (a specific SF in our case), because functionalities only define desired behaviors. For this reason, in our study we made the concept of an SF explicit in the KBMS method. However, the PISa rating process was a valuable step in the prioritization of safety solutions for PTWs and a good material to design a new methodology that overcomes its weak points.

Concerning the road crash scenarios, previous European Union research projects have used the 7 PTW crash scenarios defined in the APROSYS project as starting point (e.g., PReVENT, AIDE, EASIS, GST). However, 3 of the 7 crash scenarios concentrate less than 10% of total of motorcycle crashes in European Union at that moment. This implies that more than 90% of PTW crashes (a wide variety of crash configurations) were grouped together in only 4 general crash scenarios. To address this limitation, the definition of the PTW crash scenarios of the KBMS evaluation framework contains 26 cases (Appendix A) that can be grouped as a function of the level of detail of the crash database used. Although each crash is unique, they share some characteristics that allow us to cluster/group the crash in different general crash scenarios, and more variables to describe them offer us more details/resolution in the definition of the scenario. In our study case, we used the national crash database of Italy (ISTAT) that allowed us grouping the 26 crash cases into 9 general crash scenarios (more resolution compared to APROSYS). In addition, the KBMS introduces the concept of a coverage metric. This helps to ensure a minimum of 90% of total motorcycle crashes included in the crash scenarios defined, monitoring the remaining percentage of road crashes that contains incomplete/unknown data.

An advantage of the KBMS method is the direct interpretation of the metric obtained. For example, the PISa priority list made clear which SF is more important, but it did not clarify the absolute importance of a function in quantitative terms. In the KBMS, insight on how important an SF is with respect to the others is made explicit by its numerical value. For example, in our case study, by simple numerical inspection of the metrics of the prioritized list (Table 3), we obtain that the SF "PTW autonomous braking (2.98)" is considered twice as important as the SF "Improvement of PTW conspicuity (1.42)" on Italian roads. It should be noted that low-income countries with poor infrastructure, outdated vehicles, and limited safety awareness will see different priorities. The new method can be applied to these countries when crash data are provided.

Summarizing the benefits of the KBMS evaluation framework, it overcomes common limitations such as heterogeneous road crash data collection between different countries/regions and restricted access to the databases due to sensible information about the victims involved. In particular, the segmentation of a road crash database by using a queries list can be easily replicated locally to several databases, enabling database managers to disseminate harmonized numerical information for the KBMS method.

The key points learned during our preliminary attempt to collect and store expertise in the KB of the KBMS were (a) define a common vocabulary simplifying the exchange between experts of different specializations; (b) avoid using a binary Likert-type scale in the expert assessment in order to avoid the accumulation of neutral responses in the KB; (c) define a set of guidelines (Appendix E) using in-depth crash databases to reduce the degree of variability of the assessment in the crash scenarios; and (d) a very comprehensive list of SFs for the expert assessment have the drawback to convert the evaluation of each crash scenario in a big time consuming task, and it may go against to the number of collaborators. For this reason, more research is needed in the definition of a shorter SF list to assess. The reduction of the SF list is a tradeoff between the quality of expertise collected and the time required to encode it in order to be stored in the KB of the KBMS.

We developed a new way to synergize crash data and expertise in the vehicular safety field by means of the KBMS. The KBMS is a tool for road accident research and decision making, which enables the collaboration between researchers and data sharing, maintaining critical/confidential population data in the source. The significant outcomes of this kind of collaboration are the definition of concrete goals in terms of crash avoidance and mitigation of crash consequences. The KBMS is a tool for quantitative prioritization of safety solutions, the results of which can be used by developers and industrial stakeholders interested in vehicular safety. Furthermore, a future widely accepted KBMS would be advantageous to promote throughout the whole of Europe, becoming a tool to assist policymakers in making informed decisions on safety regulations in order to make PTWs a safer means of transport.

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Table 1 Likert-type scoring scale defined to rank the benefit of the safety function in each accident scenario to analyze.

Score Value	The assessed function would … in accident avoidance / mitigation for this scenario
0	not have an effect
1	have a very little contribution
2	have a small contribution
3	have an important contribution
4	have a very important contribution

Table 2 Information retrieved after the segmentation process applied to 3 years of data from the ISTAT road accident database. Unknown cases are less than 10% of total PTW accidents each year.

Year	2010	2011	2012
Total vehicular accidents	211404	205638	188228
Total PTW accidents	71108	71790	62374

PTW accidents in a collision scenario type:			
A: intersection & angle collision	18262	18188	15145
B: intersection & sideswipe collision	5424	5641	4663
C: straight street & sideswipe collision	6001	6376	5583
D: single vehicle accident	5479	5396	4489
E: head-on collision	4811	4693	4004
F: rear-end collision	7932	8226	7089
G: hit obstacle + hit pedestrian	5320	4981	4614
H: straight street & angle collision	8317	8553	7742
I: roundabout	3090	3385	2893

Table 3 Prioritized safety solutions of KBMS-ISTAT and PISa studies. The left column is the prioritized list of SFs in the KBMS method. The KBMS metric expresses the importance of each SF (larger numbers indicate greater importance). PISa columns represent the same information in a different manner (quartiles and absolute score), allowing comparison between the KBMS-ISTAT outcomes with those of the PISa project (mark 36 means "less important").

Safety Function description	KBMS metrics	PISa ranking	
		Quartile	Absolute position
Assist the rider to perform a hard braking without falling from the PTW	3.87	Q1	7,8,9
PTW autonomous-braking	2.98	Q1	4
PTW send a signal to Slow/Stop other vehicle	2.52	Q1	1
PTW - Alert to the rider of an oncoming vehicle	2.35	Q3	21
PTW restricts its maximum speed to street top speed	2.16	Q2	14
Energy dissipation element placed in the PTW to dissipate rider kinetic energy during a crash. Case: frontal collision of the PTW	1.51	Q2 & Q3	17,18,24
Improvement of PTW conspicuously (help to be seen for others)	1.42	Q1 & Q4	6,35
Driver state detection (guarantees a minimum level of alert)	1.32	Q4	36
Other vehicle alcohol interlock	0.74	Q4	36
PTW Lane keeping	0.14	Q4	36

Figure 1 Diagram showing the entire process of prioritization. The components of the KBMS are shown in grey. Firstly, the set of queries is defined, safety functions are selected, and road crash scenarios are determined in the evaluation framework. The queries are used to extract crash information, sending it to the inference engine. Parallel in the workflow (collecting stage), the SFs are assessed in several road crash scenarios by experts, in order to obtain the contents of the KB. Finally (processing stage), the inference engine combines crash information with expert knowledge to generate a prioritized list of safety solutions, which corresponds to the country/region of the road accident data used.

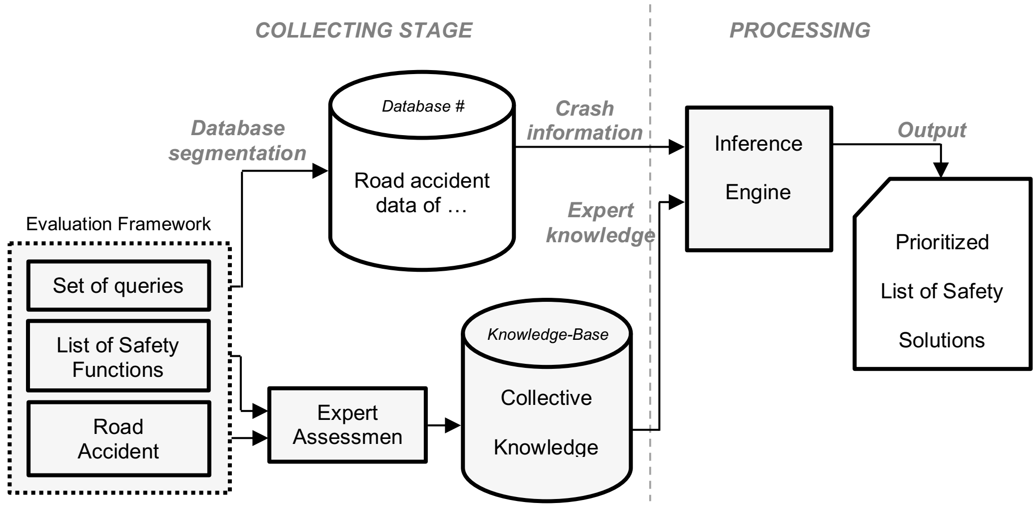


Figure 2 Representation of 5-dimensional matrix of the KB. The height of the pentagonal prism represents the storage capability of expert assessments. Each lateral face represents the index of the KB matrix.

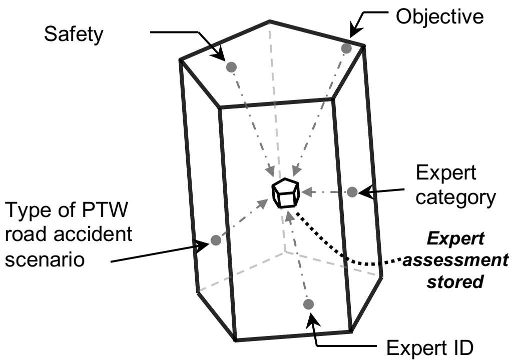
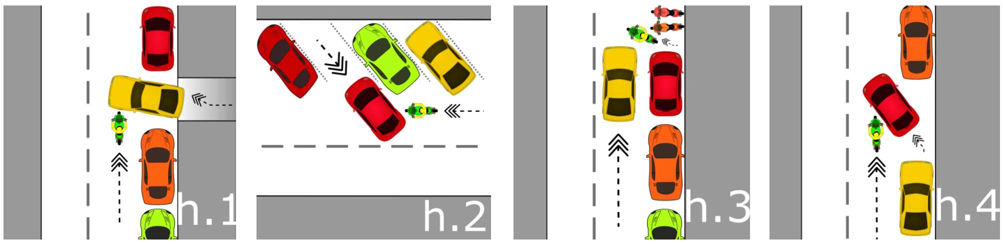


Figure 3 Example of an expert assessment of 2 SFs for parking-out maneuvers. The example corresponds to the analysis of the level of crash avoidance/mitigation of 2 SFs in the set of accident scenarios "h." The numbers in the table represent the outcome of the expert evaluation using the scoring scale defined in Table 1.



Avoidance				Mitigation				Safety Functions (SFs)
h.1	h.2	h.3	h.4	h.1	h.2	h.3	h.4	
4	3	2	4	0	0	1	2	Assist the rider to perform …
2	2	0	1	1	1	2	4	Warn to other vehicle of …
								…